Enhancing Novice Drivers' Takeover Behavior in Conditional Automated Driving: A KAP-Based Training Approach

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Abstract

Conditional automated driving, categorized as Level 3 automation by the Society of Automotive Engineers (SAE), allows drivers to fully engage in non-driving-related tasks (NDRTs) but requires them to resume vehicle control upon takeover requests (TORs). Thus, drivers' ability to quickly regain control of the vehicle is critical to driving safety. Existing training programs mostly focused on enhancing drivers' knowledge of automation or shaping their attitude toward automation, but rarely considered enhancing the takeover skills in the takeover process. In this study, we embedded a behavior spectrum within the Knowledge–Attitude–Practice (KAP) framework to enhance drivers' takeover performance. Forty-eight gender-balanced novice drivers (mean age: 22.17, range: 18-30) were assigned to one of the three training programs, i.e., baseline (BA), Knowledge–Attitude (KA), and KAP. Their takeover performance was evaluated in two takeover scenarios where drivers engaged in externally-paced and self-paced NDRTs. Drivers' eye-tracking behaviors, physiological metrics, subjective measures, and takeover performance metrics were analyzed in a driving simulator experiment. Results showed that KAP training yielded the most benefits by broadening drivers' visual scanning area (p = .049), reducing long (> 2 sec) off-road glances (p = .04), lowering subjective workload (p = .002), and producing smoother lateral control (p = .03). Both KA (p < .0001) and KAP (p < .0001) accelerated first glance on road and takeover reactions. Furthermore, KAP training was associated with a smaller increase in heart rate during takeovers than BA training (p = .04). Finally, trust did not differ across groups, suggesting that the behavioral improvements from KAP training may stem more from procedural skill improvements than from trust-related changes. These findings highlight the effectiveness of KAP training in facilitating quicker and smoother takeover actions and thus should be considered in future training programs for SAE Level 3 users.

Keywords

Automated driving, KAP Training, Takeover performance, Non-driving-related task

1. Introduction

Before fully autonomous vehicles saturate the market, drivers remain responsible for vehicle safety even when driving automation is engaged. This is especially the case in the vehicles with Level 3 automation, as defined by the Society of Automotive Engineers (SAE) (SAE International, 2018), in which the system handles all driving tasks within its Operational Design Domain (ODD) but expects the driver to intervene in emergencies. Given the gradually increasing commuting times in large cities (Engelfriet & Koomen, 2018), if drivers are freed by SAE Level 3 automation and engage in non-driving-related tasks (NDRTs), substantial social benefits can be realized. However, the engagement of NDRTs in SAE Level 3 vehicles raises concerns about whether drivers can safely regain control in time and how to support a timely and smooth transfer of control between driving automation and out-of-loop drivers.

To address this challenge, prior research has primarily focused on the design of takeover requests (TORs). For example, previous research has found that displaying the vehicle's confidence in obstacle detection can facilitate safer control transfers (Lee & Pitts, 2024), and that auditory signals can elicit shorter reaction times than tactile stimuli (Tang et al., 2020). However, when engaging with NDRTs, drivers might experience high cognitive load, leaving fewer resources available to respond to TORs (Du et al., 2020; Wang et al., 2025). For example, previous research has suggested that at least 5 seconds of TOR lead time are required for fully out-of-loop drivers to safely regain vehicle control (Kim & Yang, 2017). Thus, several studies have highlighted the importance of responsibility-oriented training. For example, DeGuzman & Donmez (2024) found that responsibility-focused training resulted in shorter takeover times than limitation-focused training.

Although driver licensing programs are mature, there are no widely agreed-upon standards for training users of driving automation; however, some countries have issued guidelines for such training. For example, in recognition of several fatal driving-automation-involved crashes in China, the Ministry of Public Security of China issued guidelines in 2025 mandating that automakers implement robust user-training programs for SAE Level 2 and Level 3 systems (China Road Traffic Safety Association, 2025). In North America, the American Association of Motor Vehicle Administrators (AAMVA) recommends promoting driver training on driving automation technologies and updating driver education curricula and educator training to cover key topics such as system capabilities/limitations, engagement/disengagement, and misuse/overreliance risks (American Association of Motor Vehicle Administrators, 2024). Similarly, Automated Driving Systems (ADS) guidance by the National Highway Traffic Safety Administration (NHTSA) also highlights "consumer education and training" as a core safety consideration . In the United Kingdom, the Department for Transport also mentioned practical user-education mechanisms when highlighting the safe use of Automated Lane Keeping Systems, including in-vehicle training modules, point-of-sale explanation/demonstration, and accessible materials (e.g., quick guides, online videos/courses, and simulators) (Department for Transport, 2021).

However, existing training primarily targets users' mental models of the advanced driving assistance system (ADAS) (Huang et al., 2024), aiming to help drivers allocate their attention appropriately, with few studies focusing on the dynamic process of shifting attention from the NDRT to the driving task. To address these gaps, we adopted the Knowledge–Attitude–Practice (KAP) framework (Hassett et al., 2022) to develop a training protocol that aims to improve drivers' takeover performance by synthesizing and extending the benefits of prior endeavors. Specifically, in KAP, knowledge provides the foundation for drivers to understand system limits and takeover triggers, similar to training programs that enhance drivers' understanding of system limitations (Noble et al., 2019). At the same time, attitude serves as the motivational factor. Echoing the findings in DeGuzman & Donmez (2024), by shaping drivers' attitudes toward their responsibility, the allocation of cognitive resources can be optimized, especially under high-load scenarios. Finally, the practice component extended beyond previous driving research and emphasizes hands-on exercises that objectively reinforce takeover maneuvers. The KAP model has demonstrated significant advantages in various domains. For example, in the health and safety sectors, Tumwine et al. (2023) found that structured training programs can improve both knowledge and attitudes, fostering safer practices. In the driving domain, the research by Fahlevi et al. (2022) showed that improving ambulance drivers' knowledge leads to better defensive driving behavior, and Tajvar et al. (2015) found that a greater awareness of traffic regulations can reduce accident risk. Similarly, a study by Jeihooni et al. (2022) found that ongoing education in taxi drivers' knowledge contributed to responsible driving practices.

In our study, we adopted the KAP framework to design a takeover training program that enhances drivers' behavior from cognitive understanding and attitudinal engagement to behavioral execution. We then validated its effectiveness when drivers were distracted by two types of NDRTs in a driving simulator experiment: self-paced non-driving-related tasks (ST) and externally-paced non-driving-related tasks (ET). We intentionally differentiated the NDRT types because ST and ET have different effects on human performance (Singer, 2000). To evaluate the effectiveness of the training, we collected behavioral, physiological, and subjective metrics as drivers handled different takeover scenarios, defined by scenario type and TOR lead times. To the best of our knowledge, this is the first study to adopt the KAP training protocol to improve takeover skills and the first to consider the pace of NDRTs in an SAE Level 3 vehicle.

2. Literature review

2.1 Takeover request (TOR) and takeover performance

The TOR lead time is crucial for vehicles with SAE Level 3 automation, in which drivers can briefly disengage but must be ready to resume control. Research indicates that shorter TOR lead times are associated with slower, more hazardous reactions, particularly when drivers engage in NDRTs such as listening to music or watching videos (Kim et al., 2021). Han et al. (2023) found that NDRTs negatively affect response times, with varying lead times showing significant performance differences. Morales-Alvarez et al. (2020) emphasized the importance of maintaining driver awareness prior to TOR, as low attention during NDRTs increases reaction times during the control transition. Research also showed that the optimal takeover performance occurred when the TOR lead time was between 10 and 60 seconds, as indicated by lower crash rates, larger minimum time-to-collision (TTC), and reduced lateral acceleration. At the same time, longer lead times (e.g., 15–60 seconds) are necessary to achieve optimal driver acceptance, although drivers can successfully resume control of vehicles with shorter lead times (e.g., 10 seconds) (Wan & Wu, 2018).

At the same time, individual differences can also affect the takeover performance. For example, in a literature review, Gasne et al. (2022) found that five of fourteen studies reported poorer takeover performance (in terms of takeover time and takeover quality) among older adults than among younger adults. At the same time, several factors, including speed, type of takeover request, duration of notification interval, and number of takeovers, were found to influence takeover performance among older adults. Moreover, Peng et al. (2022) found that age is not the sole factor distinguishing younger and older drivers; individual cognitive differences, such as variations in executive function, have been shown to influence takeover performance, with more stable vehicle control observed among those who exhibited higher executive function abilities

2.2 Training of driving automation users

Previous research has predominantly focused on drivers' awareness of the automation limitations. However, studies have shown that while understanding system limitations is important, it is not sufficient to ensure safe takeovers. For example, Boelhouwer et al. (2019) and Forster et al. (2019) found that while text-based manuals can provide basic information about the system's capabilities and limitations, they may not be sufficient to prepare drivers for real-time takeovers in complex driving scenarios. Further, Krampell et al. (2020) found that awareness of automation limitations may even reduce drivers' willingness to rely on the system, potentially leading to underutilization of automation. Similarly, DeGuzman & Donmez (2024) found that the limitation-focused training can lead to decreased interest in using ADAS, particularly among novice users. Thus, responsibility-focused training might be a better solution. For example, DeGuzman & Donmez (2024) found that enhancing drivers' awareness of their role in using automation can lead to more effective takeover behavior. Zheng et al. (2023) also highlighted that a clear emphasis on the driver's responsibility during takeovers can help mitigate the drawbacks of limitation-based training and foster a healthier relationship between drivers and automated systems.

However, these approaches primarily aim to encourage drivers to pay greater attention to the driving task and avoid NDRT engagement, but they can hardly improve drivers' ability to refocus on the road when they are permitted to be distracted, as in SAE Level 3 vehicles. In such cases, the KAP framework may provide a more comprehensive solution by enhancing drivers' knowledge of the takeover process, promoting appropriate attitudes toward attention allocation, and offering practical strategies for effective attention switching.

2.3 The influence of NDRTs on takeover performance

In the context of conditional automation, prior studies have shown that engaging in NDRTs can adversely affect takeover performance. For example, Liu et al. (2024) found that different NDRTs exert different influences on takeover performance, with texting and conversing resulting in the poorest performance. Similarly, Lin et al. (2020) found that visual NDRTs, such as reading news or watching videos, can delay drivers' responses to TORs, diminishing the takeover quality in safety-critical scenarios. Another meta-analysis by Zhang (2024) revealed that both visual-cognitive-motor and visual-cognitive NDRTs can delay takeover actions, with visual-cognitive-motor tasks having a stronger effect.

However, the existing literature has primarily focused on the effects of distractions without distinguishing among their paces. The ST, such as texting, can be paced by the driver and is driven by internal motivations, whereas the ET, such as handling incoming calls, in contrast, can hardly be paced by the driver. As a result, the ET is less controllable by the driver and may have a greater impact on driving performance. The differences in how these NDRTs affect driver performance in takeover events remain underexplored. This represents a gap in the literature, as conditional automation introduces new dynamics in which drivers must quickly regain control after engaging in ST or ET.

2.4 Synthesis of previous research and the current study

Taken together, previous literature points to two major interconnected gaps that motivate the present study. First, training programs have predominantly targeted drivers' knowledge of system limitations or their awareness of responsibility, with little attention to the procedural skills required during the takeover process. Second, studies examining NDRTs have largely treated distraction as a unitary construct in the context of driving automation, without distinguishing between self-paced and externally-paced tasks, which differ in their temporal controllability. Thus, the present study addresses these two gaps by embedding a behavior-spectrum practice component within the KAP framework and evaluating its effects across both self-paced and externally-paced tasks when driving with automation, using a comprehensive set of indicators, including the driving performance measures, visual attention allocation indicators, and subjective questionnaire data.

3. Method

3.1 Participants

In this study, to control for the variability within the samples, we focused on novice drivers, as they were found to have worse takeover performance compared to experienced drivers (Zhang et al., 2023), more likely to exhibit risky distraction behaviors in vehicles with driving automation (He & Donmez, 2019), and more inclined to adopt new technologies, such as driving automation. Therefore, a total of 48 novice drivers, consisting of 24 males and 24 females with an average age of 22.17 years (standard deviation: 2.82, min: 18, max: 30 years), were recruited through both online posters and offline advertisements. Given that our program targets the new users of ADAS, the eligibility criteria included holding a valid C1/C2 driver's license in China within one year, having no prior experience with ADAS features (including Lane Centering Control, Adaptive Cruise Control, or other more advanced ADAS functions such as automated lane-changing), and drove less than 5,000 kilometers in the past year. Table 1 presents descriptive statistics and comparison results for demographic characteristics across experimental conditions. A t-test indicated no significant age difference was observed across experimental conditions (p > .05). Participants were informed that they would receive compensation of 80 RMB per hour. The study was approved by the Hong Kong University of Science and Technology (HREP-2022-0158).

Table 1. Descriptive statistics of the demographic information in different experimental conditions.

Conditions	BA training	KA training	KAP training
Number of participants (M; F)	16 (M: 8; F: 8)	16 (M: 8; F: 8)	16 (M: 8; F: 8)
Mean Age (years; min, max, SD)	22.44 (18, 28, 2.67)	22.69 (18, 30, 3.80)	21.38 (18, 28, 1.11)

Note: BA - baseline, i.e., no training, KA - knowledge and attitude; KAP - knowledge, attitude, and practice; N - number of participants; M - males; F - females; Min - minimum; Max - maximum; SD - standard deviation.

3.2 Apparatus

The experiment was conducted using a fixed-base driving simulator (Figure 1) featuring three 43-inch screens, offering a horizontal viewing angle of 150° and a vertical angle of 47°. Participants could activate the driving automation system by pressing virtual buttons on a 15-inch screen located beside the steering wheel. To disengage the automation, participants could either press another virtual button, turn the steering wheel, or use the brake pedal. Driving data was recorded at 60 Hz with the SILAB 7.1 simulation software from WIVW GmbH. Physiological data were collected using sensors from Ergoneers GmbH at a sampling rate of 500 Hz. Eye-tracking data were obtained using the Smarteye system at 60 Hz. All data streams were synchronized with the Human Research Tool (HRT) software by Info Instrument.

Figure 1. Driving simulator, eye-tracker, and physiological sensor placements.

3.3 Design of the KAP training program

This study employed three variations of the training program: (1) baseline (BA), which provided only basic knowledge on how to use ADAS; (2) KA training, which provided knowledge and attitude training; and (3) KAP training, which included both KA training and practice training. Figure 2 provides an overview of the KAP training program, including duration, delivery mode (instructor-led vs. self-guided), and activity type (passive vs. active) of each component:

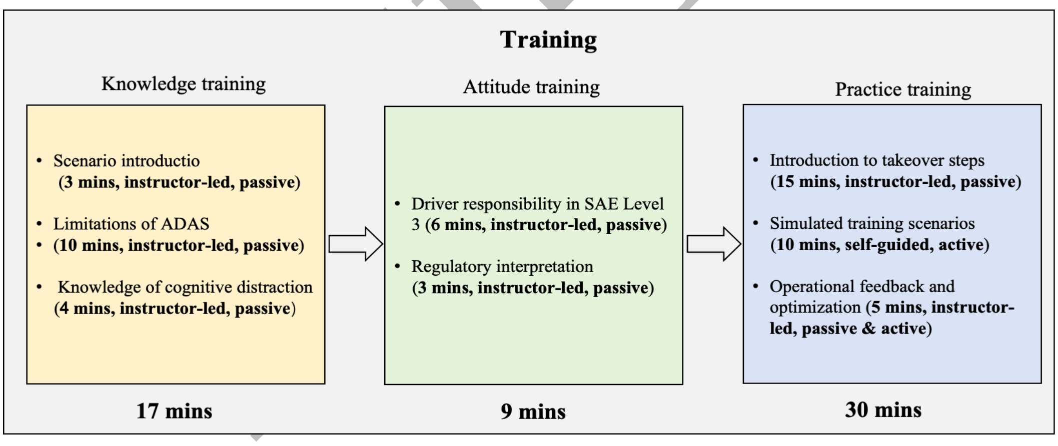


Figure 2. The duration, delivery mode, and activity type of each training component. In the figure, instructor-led means that the training was facilitated and guided by an instructor; self-guided means that participants independently completed the tasks or activities based on pre-provided materials or instructions; passive means that participants mainly received information through observation or listening, without active engagement; and active means that participants engaged directly in tasks, applying their knowledge or skills through practice.

3.3.1 Knowledge training

The objective of this part was to ensure that novice drivers understood the limitations of conditionally automated driving systems and the impact of high cognitive load on takeover performance. To achieve this, the training followed several steps:

(1) Scenario introduction: Inspired by Zhou et al. (2024), the training began by presenting recent crashes involving driving automation. Participants were then prompted with open-ended questions (e.g., perceived contributing factors, risks, and lessons learned) and engaged in a brief guided discussion to express their perspectives.

(2) Limitations of ADAS: The overview of the various levels of driving automation and their corresponding definitions was presented according to the Society of Automotive Engineers (SAE) (J3016, 2018). We then provided a detailed analysis of the characteristics of conditionally automated driving (SAE Level 3), focusing on its operational design domain, attention allocation requirements, and takeover demands, and highlighting the distinctions between this level and other levels of automation.

(3) Knowledge of cognitive distraction: The concept of cognitive distraction was explained, with particular emphasis on its potential effects on takeover performance, given that cognitively demanding NDRTs are common in SAE Level 3 vehicles (e.g., answering phone calls or attending an online meeting). An analysis of typical task-switching scenarios under high cognitive load was then presented, which aided in understanding how to assess task priorities and swiftly recover essential tasks during task interruptions. To further illustrate these concepts, case studies, including the 1987 MD-82 aircraft accident in Michigan ("Northwest Airlines Flight 255," 2025), were utilized to demonstrate typical scenarios of task interruptions.

3.3.2 Attitude training

This part aimed to enhance drivers' understanding of their responsibilities and the potential risks associated with ADAS. The training included the following steps:

(1) Introduction of driver responsibility in SAE Level 3 vehicles: By analyzing accident case videos and investigative reports (Vlakveld et al., 2011), the training highlighted the limitations of driving automation, helping drivers recognize the safety risks if failing to fulfill

supervisory duties.

(2) Regulatory interpretation: By analyzing relevant Chinese regulations regarding liability when driving with automation, this step ensured that drivers were clear about their legal responsibilities in the event of an accident, especially the legal consequences when they failed to react promptly during takeover scenarios.

3.3.3 Practice training

The objective of this part was to provide systematic operational training, ensuring drivers could execute takeovers decisively and consistently in real-world driving scenarios. Such practice has been found to facilitate the effective execution of takeover maneuvers even under high taskloads (Gao et al., 2024). The training process included the following steps:

(1) Introduction to takeover steps: Drivers were introduced to the takeover steps based on a three-stage operational skills model (Figure 3), informed by established frameworks in the takeover literature (Endsley, 1995; Gold et al., 2013; Eriksson & Stanton, 2017; Zeeb et al., 2015; Gao et al., 2024). Step 1 focused on situation awareness reconstruction, an initial cognitive stage in which drivers disengaged from the NDRT and quickly rebuilt an understanding of the driving context by scanning key areas. Steps 2 then represented two alternative disengagement modes, depending on the driver's preferred strategy: (i) control input (e.g., pressing the brake pedal and/or turning the steering wheel; (ii) button press (i.e., shifting gaze to and pressing the automation switch on HMI). Step 3 was the subsequent post-disengagement stage, during which drivers monitored the evolving traffic situation and selected appropriate maneuvers (e.g., braking, lane change, or acceleration). After receiving guidance and skill instruction, drivers practiced these steps.

(2) Simulated training scenarios: Drivers were familiarized with the takeover task they must perform during takeover scenarios, aiming to facilitate quick, confident takeover decisions in complex driving environments and effective control of the vehicle's movement. The takeover maneuvers were repeated four times to reinforce the drivers' ability to execute tasks reliably under high cognitive load.

(3) Operational feedback and optimization: Following every simulated training trial, drivers received immediate feedback on their performance, including response time and accuracy of takeover operation. This feedback loop was designed to continuously optimize their performance.

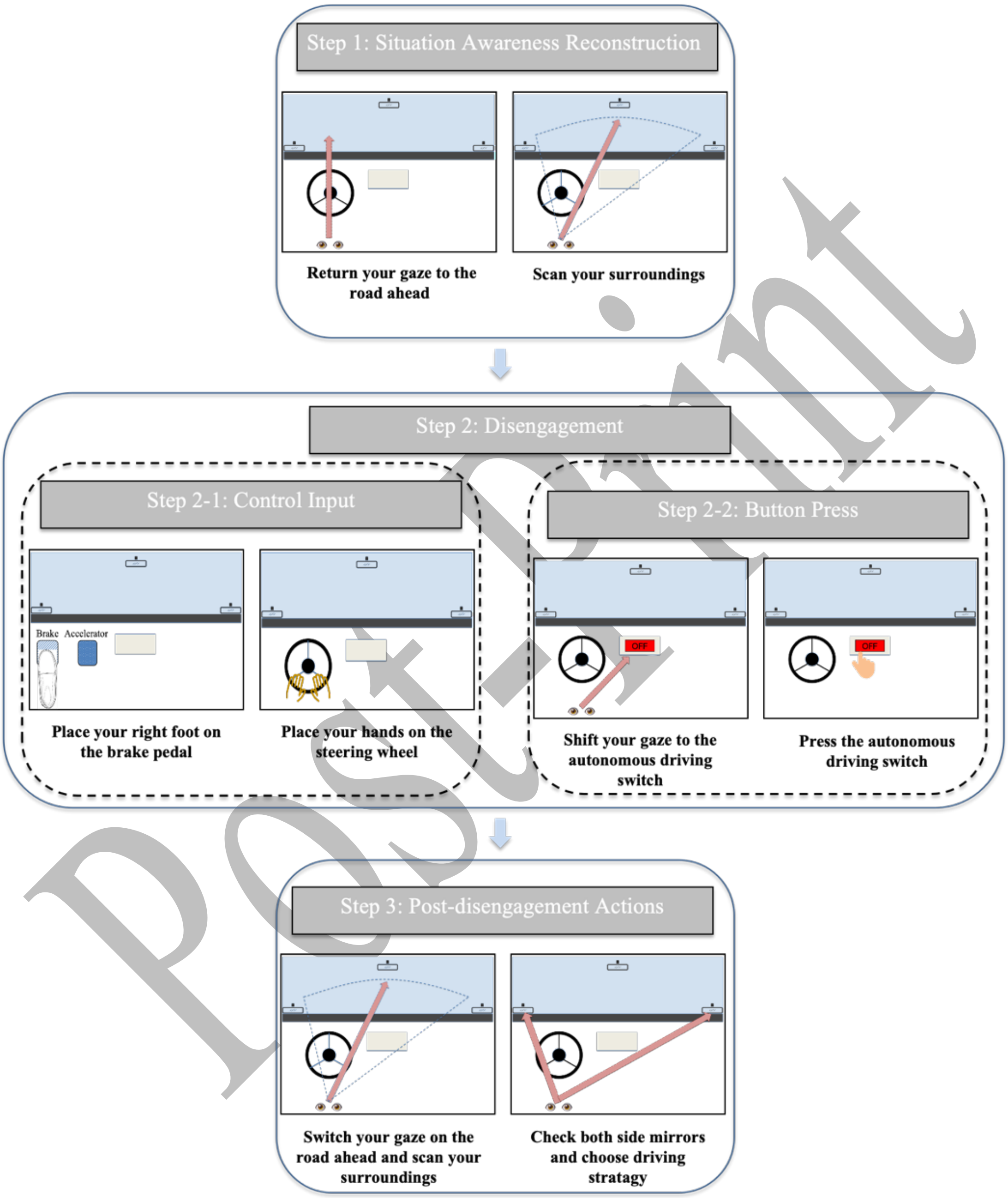


Figure 3. Schematic diagram of the stepwise decomposition of takeover behavior.

3.4 Driving and takeover tasks

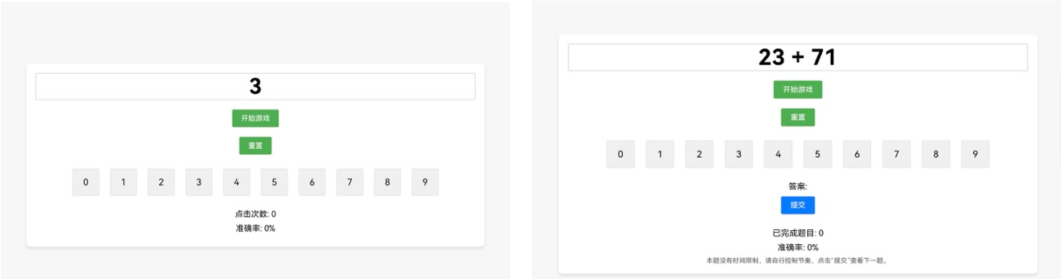
Each participant drove once on a bidirectional six-lane road, with a speed limit of 120 km/h. They were informed that the vehicle was equipped with SAE Level 3 driving automation. Thus, participants' driving task in the experiment was to supervise and operate the SAE Level 3 vehicle during the simulated drive. At the same time, they were informed of the possible takeover tasks in the drive. Specifically, as shown in Figure 4, there were two types of takeover scenarios that would require participants to take back control of the vehicle: 1) bypassing a construction zone, where the driver must change lanes to avoid the construction area; and 2) driving in a dense foggy region. The takeover lead times were set to 6 s and 10 s before a crash or entering the foggy zone, the respective minimum thresholds at which driver acceptance and driving performance can decline significantly (Wan & Wu, 2018). In the drive, participants were also instructed to use the automation as much as possible, remain in the middle lane, and take manual control only when necessary or after an auditory TOR (i.e., "Construction/foggy region ahead, please take over in 6/10 seconds").

(a) (b)

Figure 4. Takeover scenarios: (a) the construction area, and (b) the dense foggy region.

3.5 Non-driving-related tasks (NDRTs)

We designed both ST and ET to investigate the effect of training on participants' takeover performance while they are engaged in these two types of NDRT tasks. Specifically, the ST was a self-paced mathematical task consisting of 2-digit calculations with no time limit, allowing participants to pause at any time. The ET was a numerical 1-back task, where participants had to remember and select the number preceding the current one. As shown in Figure 5, both the mathematical and 1-back tasks were visual-manual cognitive tasks that required participants to be visually and manually distracted from driving, simulating typical high-cognitive-load scenarios (e.g., answering a phone call or working on work-related documents) in SAE Level 3 vehicles.



(a) (b)

Figure 5. Non-driving-related tasks: (a) externally-paced 1-back task (ET), (b) self-paced 2-digit mathematical task (ST).

3.6 Experiment design

To investigate the impact of different training methods on the performance of novice drivers when facing various NDRTs and TOR lead times, this study employed a 2×2×3 mixed design. In this design, the three levels of training methods were treated as a between-subjects factor, whereas the two levels of NDRTs (ET vs. ST) and the two levels of TOR lead time (6 seconds vs. 10 seconds) were treated as within-subject factors. The order of the within-subject factors was counterbalanced using a Latin square design, yielding four experimental orders (with a base order of ET+6 seconds, ET+10 seconds, ST+6 seconds, and ST+10 seconds). Further, participants were stratified by gender and assigned to one of the three training groups and one of the four experimental orders via blocked randomization. Such a design resulted in two males and two females in each combination of experimental order and training group (see Table 1), yielding 48 participants (2 participants per gender × 2 genders × 3 training methods × 4 orders) in total. Allocation was not concealed from the experimenter (who delivered the assigned training), but participants were not informed of alternative training or of the study hypotheses.

3.7 Procedures

Participants were instructed to maintain a regular sleep schedule, refrain from alcohol, and avoid caffeine within 24 hours prior to the experiment. Upon arrival, they signed a written consent form, completed a personal information form, and received a 30-min introduction covering the procedure, vehicle operation, and NDRT tasks. Next, a practice driving session was conducted, during which each participant encountered a TOR on the highway. Then, participants received specific training based on the experimental condition to which they were assigned. Prior to the formal experiment, eye-tracking equipment was calibrated. During the experiment, each participant experienced four takeover events, each occurring on a straight section of road. After each takeover event, participants stopped to complete the NASA Task Load Index (NASA-TLX) questionnaire to assess perceived workload during the takeover (Hart & Staveland, 1988), and a trust questionnaire adapted from Wang et al. (2025) (see Table 2), who adopted the scale for autonomous driving scenarios based on the one by Manchon et al. (2022), to assess users' trust in driving automation.

3.8 Dependent variables (DVs)

As shown in Table 2, the DVs of interest include drivers' visual behavior, takeover performance, physiological response, and subjective measures. The data extraction periods for the variables are provided in Figure 6. Specifically, the "1-Start" denotes the point at which the NDRTs begin. The "2-TOR" is the moment when the TOR was initiated. The "3-Automation Disengagement" was defined as the moment the driver disengaged the automation. The "4-Takeover event ends" was defined as the endpoint of the heavy fog area or construction area. The duration of 1-2 was the same for all participants.

Regarding the visual behaviors, as illustrated in Figure 7, we were interested in drivers' visual attention to five areas of interest (AOIs), including the road ahead, the rear-view mirrors, the sky and roadsides, the interaction screen where the NDRTs were provided, and the dashboard. Following the ISO 15007–1:2013(E) standard, each glance was defined as the moment the gaze started to move towards the AOI until it started to move away from the AOI. Glances shorter than 100 ms were excluded from analysis (Crundall & Underwood, 2011). It should be noted that the trust variable was not included in Figure 7, as it reflects users' overall trust in driving automation and was not associated with specific stages of driving.

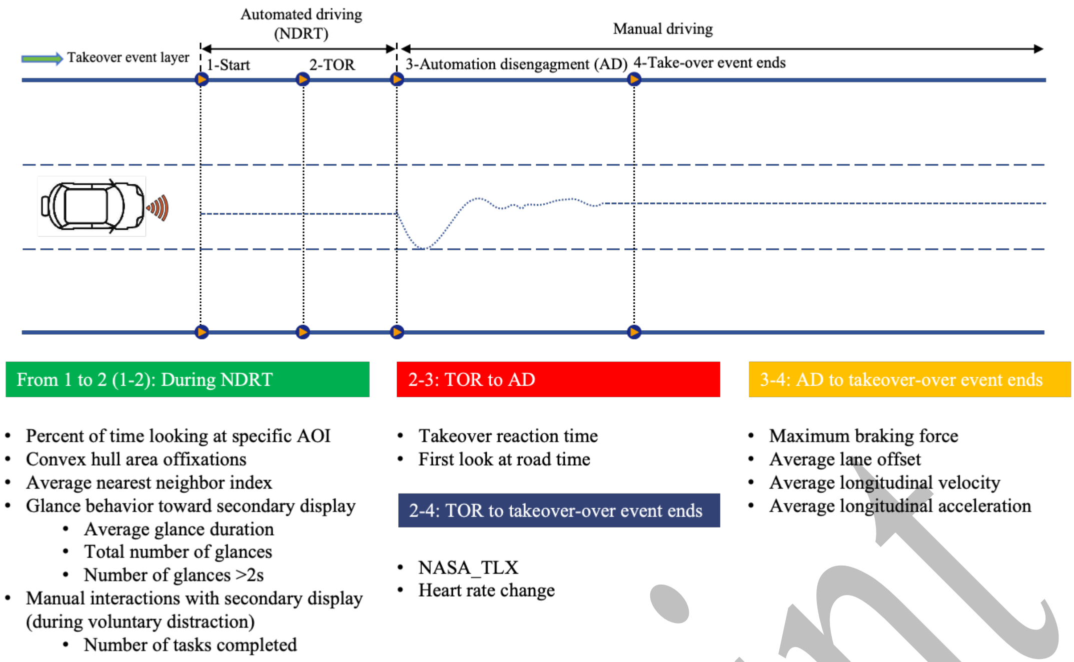


Figure 6. The extraction of dependent variables. NDRT - non-driving-related tasks; TOR - takeover request; AOI - Area of interest. Besides, the "1-Start" marks the moment when the NDRTs begin. The "2-TOR" is the moment when the TOR was initiated. The "3-Automation Disengagement" was defined as the moment the driver disengaged the automation. The "4-Takeover event ends" was defined as the endpoint of the heavy fog area or construction area.

Figure 7. Five areas of interest (AOIs) for eye-tracking analysis: road ahead, rear-view mirrors, sky/roadsides, NDRT interaction screen, and dashboard.

Table 2. Description of DVs.

Categories	**DVs**	**Unit**	**Description**	**References**
Visual behavior	Percent of time looking at specific AOI	%	The percent of the time looking at the specific AOI.	(Gao et al., 2024; Huang et al., 2024; Zhang et al., 2024)
	Number of NDRT completed	count	The number of ST completed before TOR.	(Chen et al., 2018)
	Average glance duration	s	The mean duration of glances toward the NDRT display.	(Chen et al., 2018; DeGuzman & Donmez, 2024)
	Total number of glances	count	The total number of glances toward the NDRT display.	(Chen et al., 2018)
	Number of long (>2s) NDRT glances	count	The total number of longer than 2 sec glances toward the NDRT display.	(Chen et al., 2018)
	Convex hull area of fixations	pixels	The minimum convex area that contains the fixation points	(Moacdieh & Sarter, 2015)
	Average nearest neighbor index of fixations	-	The ratio of the average distance among observed fixations and the expected mean distance of fixations given random distribution.	(Illian et al., 2008)
Takeover performance	First look at road time	s	The time of sight return to the road from the NDRT display.	(Gao et al., 2024)
	Takeover reaction time	s	From the moment the TOR is initiated to the deactivation of the driving automation.	(Wang et al., 2025; Zhang, 2024)
	Maximum braking movement	%	The maximum braking movement during the takeover process.	(DeGuzman & Donmez, 2024)
	Average lane offset	m	The mean lateral distance from the centerline of the lane.	(Gao et al., 2024)
	Average longitudinal velocity	m/s	The mean longitudinal vehicle speed.	(Zhou et al., 2024)
Workload	NASA-TLX	0-20 scale	The overall weighted NASA-TLX score during the takeover process.	(Hart & Staveland, 1988; Wang et al., 2025)
	Heart rate change	beats/min	The difference between the heart rate (HR) during the takeover period and the HR within the first one minute of the corresponding	(He et al., 2019)

			drive. Note that the HR was derived from ECG based on R-wave detection using an enhanced Pan–Tompkins algorithm (Sathyapriya et al., 2014) after a band-pass filter (3–45 Hz).	
Drivers' trust in the driving automation	Trust	-	The mean of all items, reflecting overall trust in the automated driving system, ranging from 1 to 7: the larger the values, the higher the trust. • "I would feel safe in the vehicle with driving automation." • "The driving automation provides me with more safety compared to human drivers." • "I would trust the decisions of the driving automation in most situations" • "If the traffic conditions are complex, I will not use the driving automation." • "If the weather conditions are terrible (e.g., fog, glare, and rain), I will not use the driving automation." • "Rather than monitoring the traffic environment, I can focus on other activities confidently."	(Wang et al., 2026; Manchon et al., 2022)

3.8 Statistical analyses

All statistical analyses were conducted in SAS on demand. For continuous variables, linear mixed models (LMM) were built using the PROC MIXED procedure. For count data, the negative binomial or Poisson models were built using the PROC GENMOD procedure, depending on the over-dispersion of the samples. Due to non-normality and the bounded nature of the data, maximum braking movement was modeled using Beta regression after normalization, with zeros replaced by $\varepsilon = 10^{-6}$ (i.e., $y^{**} = \max(y, \varepsilon)$). No upper-bound adjustment was conducted because all maximum braking movement was < 1 (max=0.97). The PROC GLIMMIX in SAS was adopted for Beta regression. Model assumptions for LMM were evaluated based on Q-Q plots and residual-versus-fitted plots, while assumptions for GIMMIX were checked based on standard fit metrics, including AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), and residual diagnostics.

For the dependent variables, Percent of time looking at specific AOIs, Average Glance Duration, Total Number of Glances, and Number of long (>2s) NDRT glances, the independent variables (IVs) were training method (i.e., BA, KA, and KAP), task type (i.e., SP vs. EP), and their two-way interactions. For the Number of NDRT Completed and Trust, the only IV was the training method. For the remaining variables, the IVs included training method, task type, and TOR lead time (i.e., 6 seconds vs. 10 seconds), along with their two-way interactions. It is important to note that we did not conduct post-hoc comparisons for different task types or TOR lead times, as the primary focus of this study was to investigate the effects of different training methods. Thus, if no effects of training were observed for a dependent variable, we will only report model results of the dependent variable in tables, but will not report post-hoc effects of the model (i.e., for Maximum braking movement). The generalized estimating equation (GEE) model accounted for the repeated measures (Zeger et al., 1988). Tukey-Kramer post-hoc tests (Kramer, 1956) were conducted for significant ($p < .05$) variables. Partial data missing due to sensor dropouts were handled by maximum likelihood estimation (MLE). This approach enabled the model to estimate parameters from the available data without discarding participants with missing values.

4. Results

4.1 Visual attention and NDRT engagement

Table 3 summarizes the statistical results for the visual attention metrics and NDRT engagement metrics.

Table 3. Statistical results of training and task type on visual attention-related DVs.

DVs	IVs	F/χ² value	*p*-value
Convex hull area of fixations (piels)	Training method	F(2, 154) = 15.91	**<.0001**
	Task type	F(1, 154) = 10.17	**.002**
	Training method × Task type	F(2, 154) = 3.69	**.03**
Average nearest neighbor index of fixations	Training method	F(2, 154) = 3.87	**.02**
	Task type	F(1, 154) = 1.92	.2
	Training method × Task type	F(2, 154) = 1.69	.2
Average glance duration (s)	Training method	$\chi^2(2) = 1.16$	.6
	Task type	$\chi^2(1) = 1.57$	.2
	Training method × Task type	$\chi^2(2) = 1.38$	.5
Total number of glances (count)	Training method	$\chi^2(2) = 11.01$	**.004**
	Task type	$\chi^2(1) = 0.45$	.5
	Training method × Task type	$\chi^2(2) = 1.50$	.5
Number of long (> 2 sec) NDRT glances (count)	Training method	$\chi^2(2) = 9.26$	**.01**
	Task type	$\chi^2(1) = 0.85$	.4
	Training method × Task type	$\chi^2(2) = 3.35$	.2
Number of NDRT completed (count)	Training method	$\chi^2(2) = 15.64$	**.0004**

Notes: × means the interaction effect; The bold font indicates significant results ($p < .05$).

Convex hull area. As shown in Table 3, the interaction between training method and task type significantly influenced the convex hull area. As shown in Figure 8, when performing ST, drivers who received KAP training exhibited the largest *convex hull area* (KAP vs. KA: estimated difference (Δ) = 0.21, 95% confidence interval (95%CI): [0.11, 0.32], t(154) = 5.86, p = 0.001; KAP vs. BA training: Δ = 0.1, 95% CI: [0.0001, 0.19], t(154) = 2.88, p = .049). At the same time, KA training also led to a larger *Convex hull area* than BA training (Δ = 0.19, 95%CI: [0.08, 0.31], t(154) = 4.85, p < .0001). When performing ET, no significant differences were observed between training methods (p > .05).

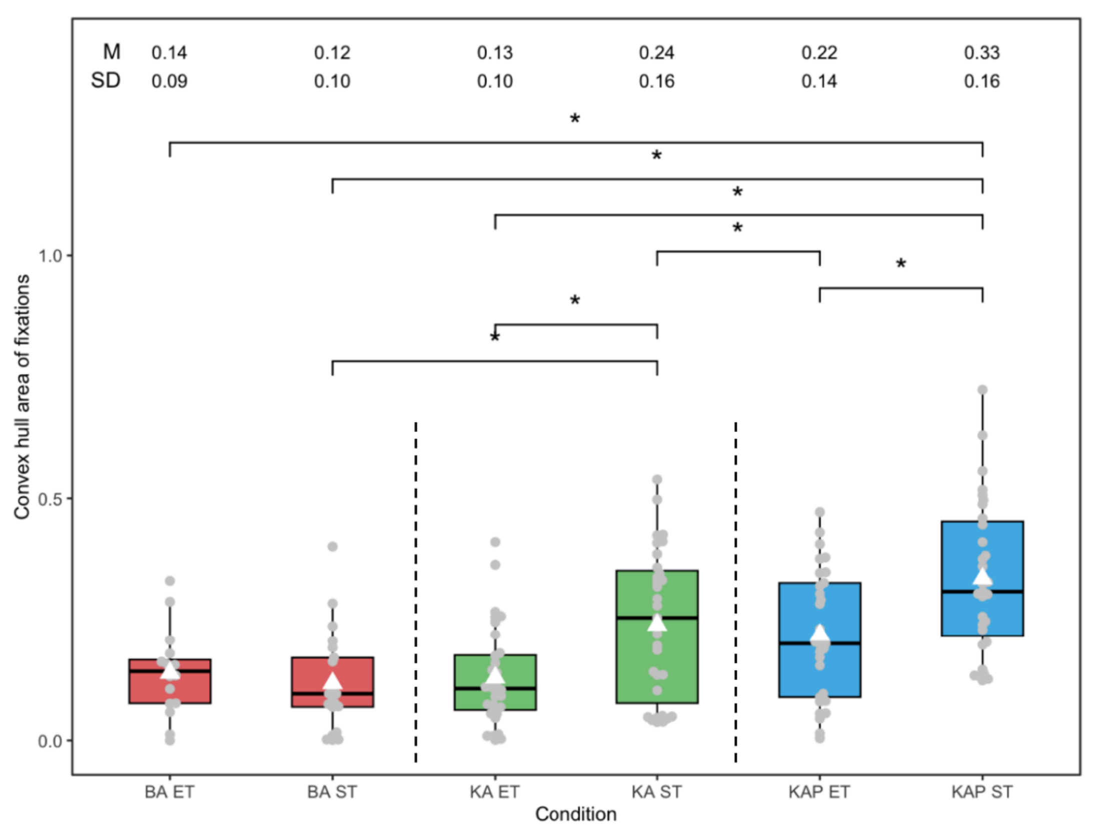


Figure 8. Post-hoc comparisons of training and task type on convex hull area. In this figure and the following figures, BA stands for baseline training; KA stands for knowledge and attitude training; KAP stands for knowledge, attitude, and practice training; ET stands for externally-paced task; ST stands for self-paced task. "*" means p < .05. The boxplot represents the 1st quantile, median, and 3rd quantile; the triangles are the means of groups.

Average nearest neighbor index. The training method significantly influenced the average nearest neighbor index. As shown in Figure 9, drivers who received KAP training exhibited a larger average nearest neighbor index than those who received BA training (Δ = 3, 95%CI: [0.44, 5], t(157) = 2.8, p = .02). No other significant differences were observed.

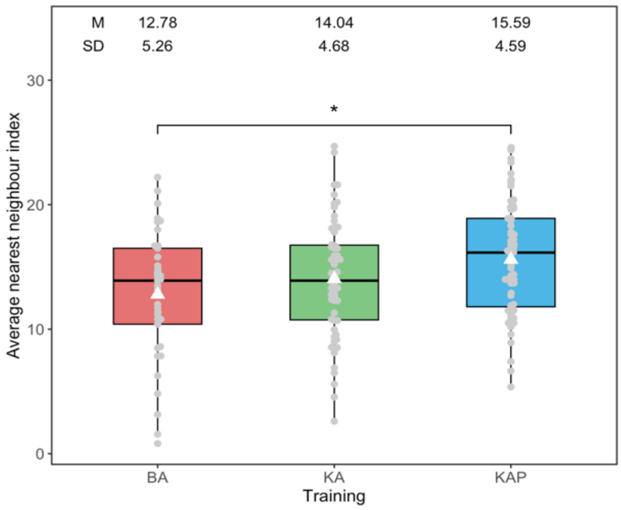


Figure 9. Post-hoc comparisons of training on the average nearest neighbor index.

Total number of glances. The training method significantly influenced the total number of glances to the NDRT display. As shown in Figure 10, drivers who received KAP training exhibited smaller total number of glances than those who received KA training (Δ = 0.47, 95% CI: [0.14, 0.81], z = 3.28, p = .003), and BA training (Δ = 0.54, 95% CI: [0.18, 0.90], z = 3.49, p = .0014). No significant difference was observed between KA training and BA training.

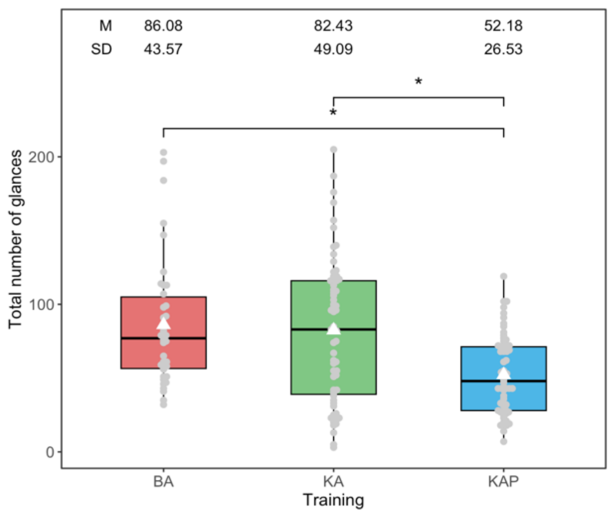


Figure 10. Post-hoc comparisons of training on the total number of glances.

Number of long (> 2 sec) NDRT glances. The training method significantly influenced the Number of long (> 2 sec) NDRT glances. As shown in Figure 11, participants who received BA training exhibited more number of glances over 2 seconds than those who received KA training ($\Delta = 0.56$, 95%CI: [0.22, 0.90], $z = 3.86$, $p = .0003$), and KAP training ($\Delta = 0.31$, 95% CI: [0.01, 0.62], $z = 2.39$, $p = .04$). No significant difference was observed between KAP training and KA training.

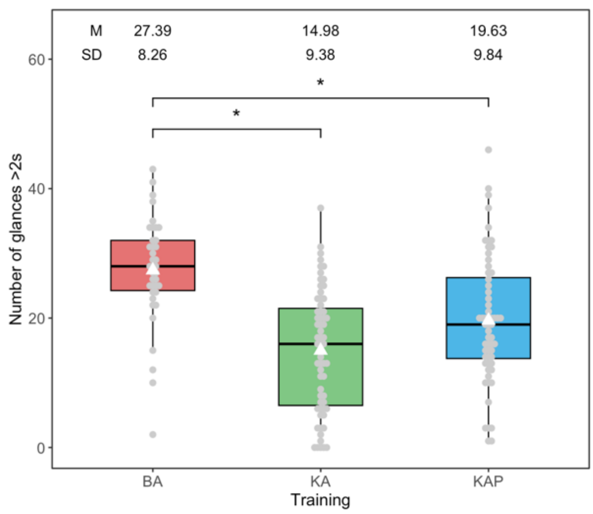


Figure 11. Post-hoc comparisons of training on the number of long (> 2 sec) NDRT glances.

Number of NDRT completed. The training method significantly influenced the number of

NDRT completed. As shown in Figure 12, drivers who received KAP training completed fewer tasks than those who received KA training (Δ = -0.59, 95 %CI: [-0.86, -0.33], z = -5.29, p < .0001), and BA training (Δ = -0.44, 95%CI: [-0.74, -0.13], z = -3.3, p = .003). No significant difference was found between KA training and BA training.

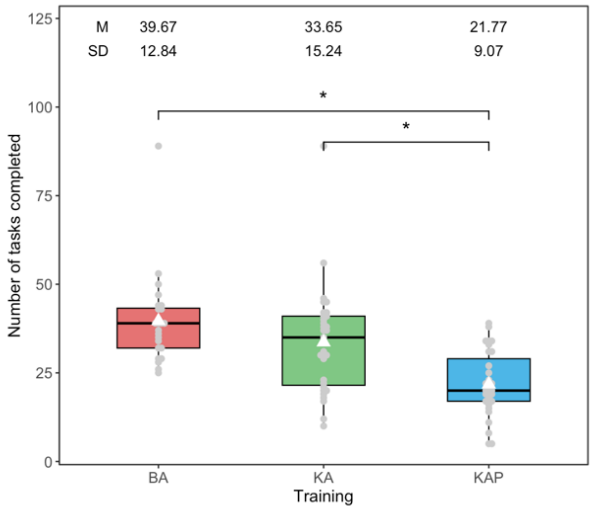


Figure 12. Post-hoc comparisons of training on the number of NDRT completed.

Percent of time looking at specific AOI. Figure 13 shows the percentage of time looking at specific AOIs across different training methods, and Table 4 summarizes the post-hoc results. It was found that, compared with participants who received BA training, participants who received KA or KAP training allocated significantly less attention to the NDRT display and more to the road ahead and the dashboard. Moreover, KAP training significantly increased attention to the rearview mirror and the roadside compared with BA and KA training.

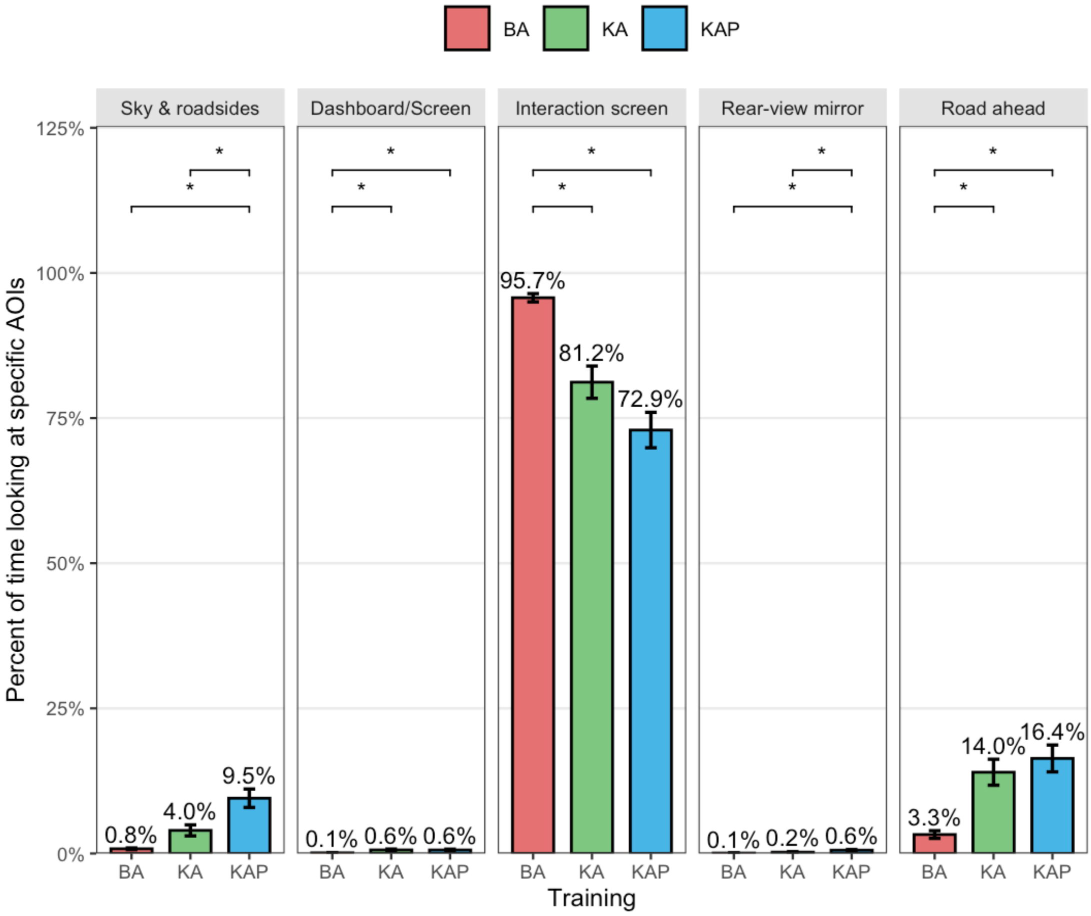


Figure 13. Description statistic of the percent of time looking at a specific AOI before TOR.

Table 4. Post-hoc comparisons of percent of time looking at specific AOI.

Main effect of Training group		Dependent variables				
		Road ahead	Rear-view mirrors	Sky and roadsides	Interaction screen	Dashboard/Screen
		F(2, 158) = 8.63 ***p* = .0003**	**F(2, 158) = 6.57** ***p* = .002**	**F(2, 158) = 12.33** ***p* < .0001**	**F(2, 158) = 14.97** ***p* < .0001**	**F(2, 158) = 3.3** ***p* = .040**
Group	Compared to Group	Pairwise comparisons of the training group on dependent variables				
BA	KA	**Δ = -10.7%** ↓ **95%CI: [-18.4%, -3.1%]** **t(158) = -3.32** ***p* = .003**	Δ = -0.2% ↓ 95%CI: [-0.5%, 0.2%] t(158) = -1.04 *p* = .6	Δ = -3.2% ↓ 95%CI: [-7.5%, 1.1%] t(158) = -1.74 *p* = .2	**Δ = 14.6%** ↑ **95%CI: [4.8%, 24.3%]** **t(158) = 3.52** ***p* = .002**	**Δ = -0.5%** ↓ **95%CI: [-1%, -0.003%]** **t(158) = -2.45** ***p* = .049**
BA	KAP	**Δ = -13.1%** ↓ **95%CI: [-20.8%, -5.4%]** **t(158) = -4.01** ***p* < .0001**	**Δ = -0.25%** ↓ **95%CI: [-0.8%, -0.1%]** **t(158) = -3.37** ***p* = .003**	**Δ = -8.7%** ↓ **95%CI: [-13.1%, -4.4%]** **t(158) = -4.73** ***p* < .0001**	**Δ = 22.8%** ↑ **95%CI: [12.9%, 32.7%]** **t(158) = 5.47** ***p* < .0001**	**Δ = -0.5%** ↓ **95%CI: [-1%, -0.002%]** **t(158) = -2.47** ***p* = .049**
KA	KAP	Δ = -2.4% ↓ 95%CI: [-9.%, 4.3%] t(158) = -0.84 *p* = .4	**Δ = -0.3%** ↓ **95%CI: [-0.6%, -0.04%]** **t(158) = -2.69** ***p* = .02**	**Δ = -5.5%** ↓ **95%CI: [-9.3%, -1.8%]** **t(158) = -3.46** ***p* = .002**	Δ = 8.2% ↑ 95%CI: [-0.3%, 16.8%] t(158) = 2.27 *p* = .06	Δ = 0.01% ↑ 95%CI: [-0.4%, 0.5%] t(158) = 0.07 *p* = .997

Notes: Table 4 summarizes the main effect of the training group and the post-hoc comparisons of the percentage of glance time allocated to each area of interest (AOI). Each column corresponds to the percentage of time looking at one of the AOIs in Figure 7. For each AOI, the first two rows report the overall main effect of the training group. The subsequent blocks present pairwise comparisons between training groups. Within each cell, Δ denotes the between-group difference computed as Group − Compared to Group, together with the associated 95% confidence interval and test statistics. Bolded values indicate statistically significant differences ($p < .05$).

4.2 Takeover performance

First look at road time. The training method significantly influenced the first look at road time (see Table 5). As shown in Figure 14, drivers who received BA training exhibited longer first look at road time than those who received KA training (Δ = 0.65, 95%CI: [0.3, 0.99], z = 4.46, p < .0001) and KAP training (Δ = 0.76, 95% CI: [0.40, 1.12], z = 4.89, *p* < .0001). No significant difference was found between KA training and KAP training.

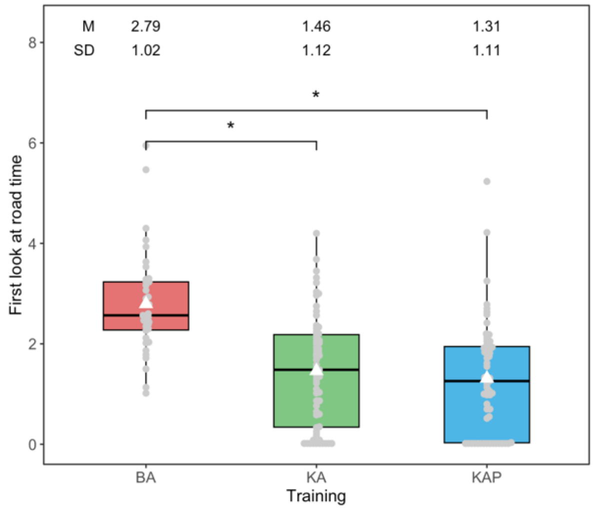


Figure 14. Post-hoc comparisons of training on first look at road time.

Takeover reaction time. The training method significantly influenced the takeover reaction. As shown in Figure 15, drivers who received BA training exhibited longer takeover reaction time than those who received KA training (Δ = 0.85, 95%CI: [0.4, 1.3], t(153) = 4.45, *p* < .0001) and KAP training (Δ = 0.82, 95%CI: [0.36, 1.27], t(153) = 4.23, *p* < .0001). No other significant effect of training was observed.

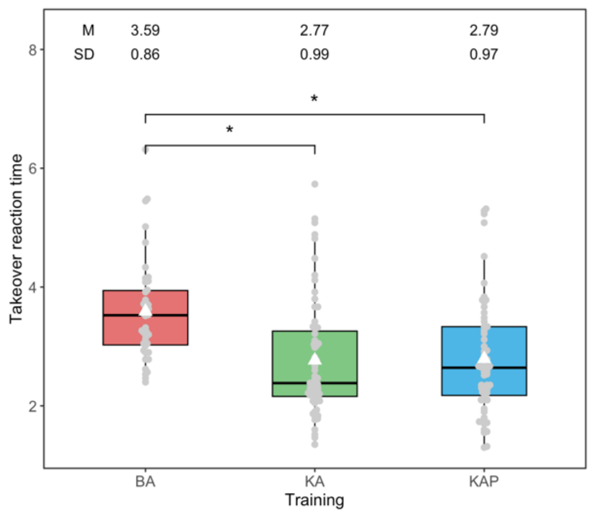


Figure 15. Post-hoc comparisons of training on takeover reaction time.

Average lane offset. The training method significantly influenced the average lane offset. As shown in Figure 16, drivers who received KAP training exhibited a smaller average lane offset than those who received BA training (Δ = -0.11, 95% CI: [-0.23, -0.01], t(150) = -2.3, *p* = .023). No other significant differences were observed.

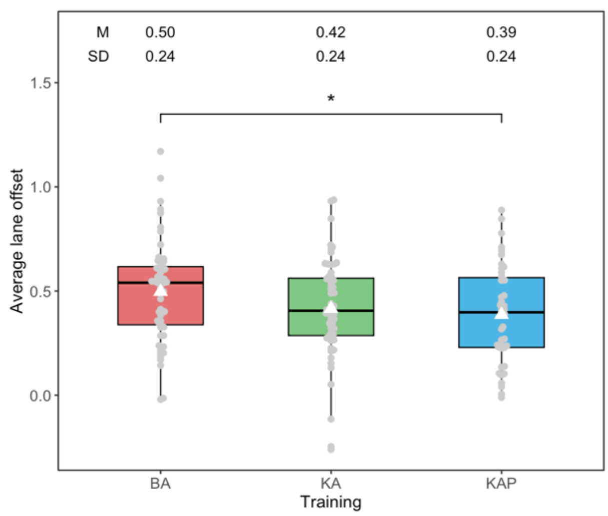


Figure 16. Post-hoc comparisons of training on the average lane offset.

Average longitudinal velocity. The training method significantly influenced average longitudinal velocity. As shown in Figure 17, drivers who received BA training exhibited larger average longitudinal velocity than those who received KA training (Δ = 0.28, 95% CI: [0.13, 0.43], z = 4.32, $p < .0001$) and KAP training (Δ = 0.22 95% CI: [0.06, 0.37], z = 3.25, $p = .003$). No other significant differences were observed.

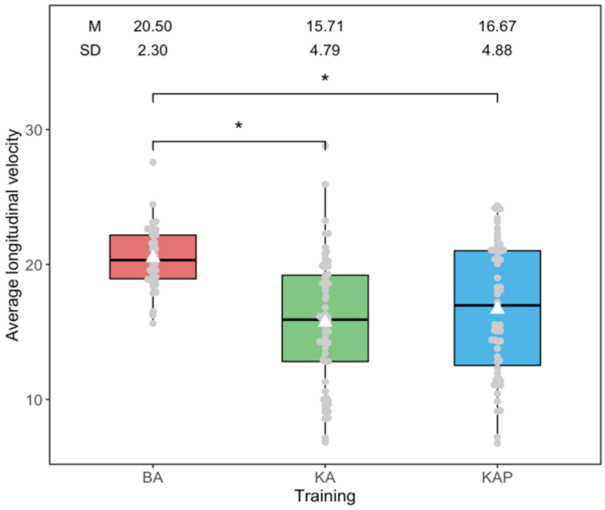


Figure 17. Post-hoc comparisons of training on average longitudinal velocity.

Table 5. Statistical results of training, NDRT type, and takeover lead time on takeover performance-related DVs.

DVs	IVs	F/χ^2 value	*p*-value
First look at road time (s)	Training method	$\chi^2(2) = 12.16$	**.002**
	Task type	$\chi^2(1) = 0.56$	.5
	Takeover lead time	$\chi^2(1) = 1.4$	.2
	Training method × Task type	$\chi^2(2) = 2.32$	.3
	Training method × Takeover lead time	$\chi^2(2) = 0.13$	.9
	Task type × Takeover lead time	$\chi^2(1) = 0.31$	.6
	Training method × Task type × Takeover lead time	$\chi^2(2) = 0.63$	.7
Takeover reaction time (s)	Training method	F(2, 153) = 11.79	**<.0001**
	Task type	F(1, 153) = 0	.95
	Takeover lead time	F(1, 153) = 3.89	**.046**
	Training method × Task type	F(2, 153) =	.9

		0.11	
	Training method × Takeover lead time	F(2, 153) = 0.43	.7
	Task type × Takeover lead time	F(1, 153) = 0.45	.5
	Training method × Task type × Takeover lead time	F(2, 153) = 2.12	.12
Maximum braking movement (%)	Training method	F(2, 39.13) = 1.78	.2
	Task type	F(1, 106.2) = 5.58	**.02**
	Takeover lead time	F(1, 107.1) = 1.80	.2
	Training method × Task type	F(2, 105.8) = 0.32	.7
	Training method × Takeover lead time	F(2, 106.8) = 0.96	.4
	Task type × Takeover lead time	F(1, 106) = .0.63	.4
	Training method × Task type × Takeover lead time	F(2, 105.6) = 2.34	.1
Average lane offset (m)	Training method	F(2, 150) = 3.08	**.049**
	Task type	F(1, 150) = 0.32	.6
	Takeover lead time	F(1, 150) = 0.16	.7
	Training method × Task type	F(2, 150) = 0.09	.9
	Training method × Takeover lead time	F(2, 150) = 0.54	.6
	Task type × Takeover lead time	F(1, 150) = .0.32	.6
	Training method × Task type × Takeover lead time	F(2, 150) = 0.2	.8
Average longitudinal	Training method	$\chi^2(2) = 14.17$	**.0008**

velocity (m/s)			
	Task type	$\chi^2(1) = 2.13$	.14
	Takeover lead time	$\chi^2(1) = 4.24$	**.04**
	Training method × Task type	$\chi^2(2) = 1.32$	.5
	Training method× Takeover lead time	$\chi^2(2) = 0.78$	.7
	Task type × Takeover lead time	$\chi^2(1) = 1.82$	.2
	Training method × Task type × Takeover lead time	$\chi^2(2) = 1.35$	.5

Notes: × means interaction effect. The bold font indicates significant results ($p < .05$).

4.3 Workload

Heart rate change. As shown in Table 6, the training method had a significant effect. Specifically, as shown in Figure 18, for those who received a KAP training, drivers who received KAP training exhibited lower heart rate increase than those who received BA training (Δ = -0.7, 95%CI: [-1.35, -0.04], $z(144) = -2.09$, $p = .04$). No other significant results were observed.

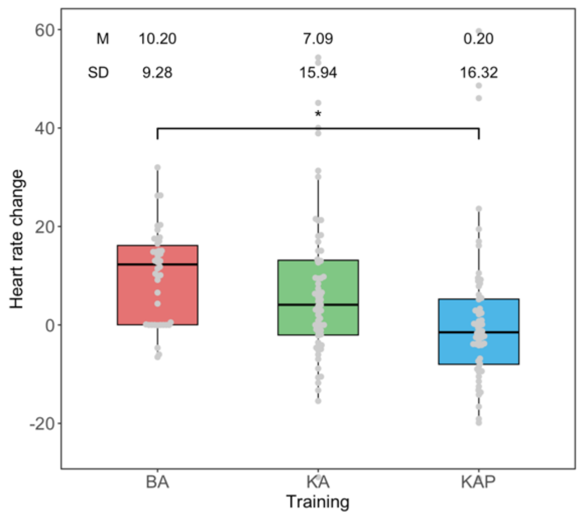


Figure 18. Post-hoc comparisons of training on heart rate change.

NASA-TLX. The training method significantly influenced NASA-TLX. As shown in Figure 19, drivers who received KAP training exhibited lower NASA-TLX than those who received

BA training (Δ = -2.4, 95%CI: [-4.03, -0.79], t(144) = -3.52, p = .002) and KA training (Δ = 1.64, 95%CI: [-3.05, -0.23], t(144) = -2.76, p = .02), no significant difference was found between BA training group and KA training group. No other significant results regarding the training method were observed.

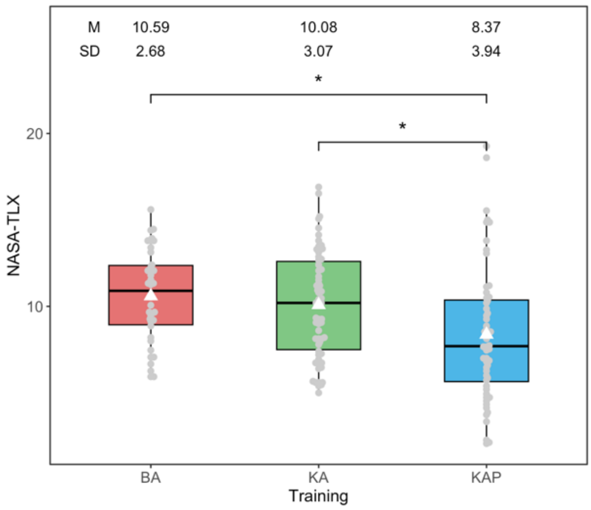


Figure 19. Post-hoc comparisons of training on NASA-TLX.

Table 6. Statistical results of training, NDRT type, and TOR lead time on workload-related DVs.

DVs	IVs	F/χ^2 value	p-value
Heart rate change (beats/min)	Training method	$\chi^2(2) = 5.52$	**.04**
	Task type	$\chi^2(1) = 3.54$	.059
	Takeover lead time	$\chi^2(1) = 0.77$	.4
	Training method × Task type	$\chi^2(2) = 1.37$	.5
	Training method × Takeover lead time	$\chi^2(2) = 4.25$	**.1**
	Task type × Takeover lead time	$\chi^2(1) = 0.74$	.4
	Training method × Task type × Takeover lead time	$\chi^2(2) = 0$	.998
NASA_TLX (0-20 scale)	Training method	F(2, 144) = 7.04	**.001**
	Task type	F(1, 144) = 14.92	**.0002**
	Takeover lead time	F(1, 144) = 0.03	.09

	Training method × Task type	F(2, 144) = 0.2	.8
	Training method × Takeover lead time	F(2, 144) = 2.04	.13
	Task type × Takeover lead time	F(1, 144) = 0	.994
	Training method × Task type × Takeover lead time	F(2, 144) = 0.39	.7

Notes: × means the interaction effect; The bold font indicates significant results ($p < .05$).

4.4 Trust in Driving Automation

No significant main effect of training method was observed for the overall trust score ($p = .2$), indicating that the training did not alter participants' overall trust in the driving automation.

5. Discussions

5.1 Effect of training on novice drivers' attention allocation strategies

First, we observed that both KA and KAP training significantly increased drivers' attention to the forward roadway compared to the baseline (Δ= 10.7% & 13.1%, respectively). The magnitude of these attention reallocations is comparable to that of visual attention shifts reported in typical distraction tasks. For example, interacting with in-vehicle systems or mobile phones has been shown to increase the proportion of fixation time away from driving-relevant areas by approximately 20%, depending on task type (Cvahte Ojsteršek et al., 2023). Such results indicate that both KA and KAP training with emphasis on attitude have successfully nudged drivers to pay more attention to driving tasks. It is possible that the attitude component recalibrated drivers' trust and perceived responsibility under conditional automation, encouraging more active supervisory monitoring. Experimental work has shown that trust-related framing and introductory information can alter reliance and monitoring patterns in automated driving (Körber et al., 2018), and that responsibility-focused training has been found to improve monitoring behavior when using automation as well (DeGuzman & Donmez, 2024). This motivational pathway provides a plausible explanation for why drivers were more willing to re-engage visually with the roadway and distribute attention more broadly after attitude-oriented training. However, the effect of KA and KAP training was more pronounced for self-paced, non-driving-related tasks, likely due to drivers' lack of control over the pace of the externally-paced task. Such detrimental effects of an externally paced task on human performance (Singer, 2000) and psychophysiological responses (Steptoe et al., 1997) have been observed in previous research.

In contrast, regardless of the types of NDRTs, KAP training led to a broader scanning area (i.e., larger convex hull area of fixations) than BA or KA training, and compared with BA and KA, KAP training yielded more attention to the rear-view mirrors and roadsides, resembling the attention patterns of professional driving instructors (Konstantopoulos et al., 2010). Such an increase in scanning breadth, reflected by a larger convex hull area of fixations and greater attention to rear-view mirrors and roadsides, is consistent with previously reported differences in visual search behavior between novice and experienced drivers and indicates that the KAP training was unlikely to have led to a cognitive tunneling effect (Dirkin, 1983) as a result of the additional trained procedures to take back the control of the vehicle. In particular, experienced drivers have been shown to distribute their visual attention more efficiently across multiple traffic-relevant areas, with greater monitoring of surrounding vehicles and lateral regions than novice drivers (Bos et al., 2015). This effect can be attributed to the explicit training on takeover procedures in the KAP training, where drivers were explicitly instructed to monitor the surrounding environment, including the rear-view mirrors, during the takeover process. It is possible that the practice component facilitated the transfer of this motivation into observable scanning behavior by strengthening procedural skill and attentional control. Structured training that combines video-based and acronym-based instruction (i.e., RUDPA: Recognize, Understand, Decide, Prepare, and Act) has been shown to improve drivers' mental models and subsequent behavior when using driving automation (Merriman et al., 2023). Previous research has also found that experienced drivers have a broader visual scanning area than novice drivers in non-automated vehicles, potentially because they have greater automated vehicle control and thus more attentional resources to allocate to environmental perception (Huang et al., 2024). In our context, hands-on practice may therefore support the formation of more stable scanning routines under takeover demands, helping drivers implement broader visual search rather than relying on a narrow, default gaze strategy. Thus, our results further demonstrate the efficacy of KAP training for novice drivers' visual attention allocation.

At the same time, both the KAP training and KA training affected users' engagement with the NDRTs. Firstly, both KA training and KAP training yielded fewer (>2 sec) NDRT glances and a smaller percentage of time spent looking at the NDRT display, indicating that the attitude-related training has encouraged users to engage less in distraction tasks. Furthermore, the KAP training led to fewer glances toward the NDRT and less engagement with the NDRT than both the KA (declined by 36.7%) and BA training (declined by 39.4%); however, no significant difference was observed between the BA and KA training in either the number of glances to NDRTs or the number of completed NDRTs. This indicates that, as a by-product of enhanced environmental monitoring, improved takeover skills may prompt drivers to shift more attention to driving-related tasks and less to distraction-related tasks. The magnitude of such a reduction in attention to distraction-related tasks is consistent with prior evidence from targeted attention training programs. For example, in a field study, novice drivers receiving FOCAL training exhibited long in-vehicle glances (≥ 2.5 seconds) in 41.9% of scenarios, compared with 60.2% in a placebo-trained group, representing an approximately 18% reduction (Pradhan et al., 2011). Similar effects were observed in simulator studies, where FOCAL-trained drivers demonstrated significantly fewer long off-road glances (between 2 and 3 seconds) (Divekar et al., 2013).

5.2 Effect of training on novice drivers' takeover performance

In our study, the KA and KAP training led to significantly shorter *first look at road time* and *takeover reaction time* than the BA training, which is comparable to the effects of structured takeover training programs that improved drivers' reaction times and attentional recovery following automation disengagement (e.g., Forster et al., 2019). We propose that the inclusion of attitude-oriented, responsibility-focused modules in both KA and KAP training fostered an internal sense of obligation among drivers and increased their alertness to takeover events. However, there was no difference in first look at road time and takeover reaction time between KA and KAP training, further supporting that attitude-oriented training, such as responsibility training (DeGuzman & Donmez, 2024), may be enough to shorten takeover reaction time.

Further, the KA and KAP training also improved takeover quality. Specifically, we found that both KA and KAP training resulted in slower vehicle speeds than BA training. Reducing speed is widely regarded as an adaptive strategy when relinquishing control from the automation (Zhou et al., 2024), and it is associated with heightened safety awareness and a more cautious response. In addition, the KAP training group also exhibited significantly smaller lateral average lane offset than the BA training group, whereas the KA group did not differ from the BA group. These results suggest that the additional behavior-spectrum practice in the KAP training enhanced drivers' vehicle control skills during takeover events, enabling smoother negotiation of the takeover zone.

The benefits of KA and KAP training are in line with recent findings by DeGuzman & Donmez (2024), who found that training improving drivers' responsibility (similar to the attitude component in KA and KAP training) can shorten their takeover response time, compared with training that only lists system limitations. However, the comparisons between the KAP and KA training in our study further expanded the findings in DeGuzman & Donmez (2024) by demonstrating the necessity of behavior-spectrum practice for ADAS users.

5.3 Effect of training on novice drivers' workload during the takeover process

Subjective workload was assessed with the NASA-TLX and heart rate change, two widely validated indices of workload demand. Drivers who received KAP training reported significantly lower NASA-TLX scores than those in either the BA or KA groups. Further, in line with the subjective workload, drivers in the KAP group also showed a smaller heart rate increase during takeover than those in the BA group, whereas no difference was observed between the KA and BA groups. This result is consistent with the change of heart rate between training and control groups (Zhou et al., 2024) and indicates that the associated behavior-spectrum training substantially reduced the workload burden during takeover. By contrast, the absence of a difference between the BA and KA groups suggests that knowledge transfer and attitude shaping alone may be insufficient to alleviate workload in high-demand takeover situations. These findings agree with Zhou et al. (2024), who applied a KAP-based intervention for nighttime hazard perception and also found that the intervention can lower drivers' heart rate and cognitive load. Our results extend prior research by demonstrating that KAP training also applies to takeover events in SAE L3 vehicles.

5.4 Cognitive mechanisms differentiating self-paced and externally-paced NDRTs

Self-paced tasks (ST) and externally-paced tasks (ET) differ fundamentally in cognitive demands. In ST, drivers maintain control over task engagement and can pause at will, thereby allowing them to monitor the driving environment as needed. In contrast, ET imposes fixed temporal demands (e.g., 1-back stimuli at fixed intervals), thereby creating a sustained cognitive load that reduces flexibility in responding to takeover requests. Though directly comparing drivers' performance between ET and ST is not a major objective in our study, we still observed a Training method × Task type interaction for convex hull area (see Figure 8). Specifically, the training facilitated a wider scanning area for ST but not for ET before the takeover events. However, we did not observe such an interaction effect for any takeover performance metrics in takeover events (see 2-3: TOR-AD in Figure 6). It is likely that without an emergent takeover event, the continuous external pace of ET impeded voluntary pauses, preventing execution of the trained strategy and thus attenuating the advantages of KAP training. This finding also aligns with previous research, which indicates that the ET can elicit a stronger stress-related physiological response than ST (Steptoe et al., 1997). Such a higher level of stress may have impaired drivers' executive functions and thus attenuated training effects. In contrast, the emergence of takeover events may have forced drivers to abandon the NDRTs immediately to quickly shift back to driving tasks, overshadowing the differences between the ET and ST.

It should be noted that, though it cannot be validated with our scenario design, better visual scanning strategies are essential for early detection of latent hazards (Sun and He, 2025; Huang et al., 2024) or silent failures (Wang et al., 2026). Thus, a more targeted strategy toward the ET distractions should be designed and validated, especially in non-urgent scenarios prior to latent hazards or silent failures. For example, in-vehicle systems can differentiate ET versus ST distractions and provide customized TOR (e.g., longer TOR lead times or stronger warnings) when possible based on real-time driver behavior (e.g., Ma et al., 2023; Sun et al., 2021; Wang et al., 2022) or emotion detection (e.g., Wang et al., 2019).

5.5 Effect of training on trust in driving automation

Across all three training groups, the overall trust score did not differ significantly, yet the KAP-trained drivers exhibited the best behavioral profile—broader scanning (see Figure 8), reduced NDRT engagement (see Figure 12), and lower workload (see Figure 19). This behavioral–attitudinal dissociation suggests that KAP training fostered skill-based self-regulation (Rasmussen, 1983): drivers held similar attitudes toward the system but exercised greater behavioral discipline. These results indicate that the behavioral benefits of KAP training were not driven by suppressed trust but by improvements in procedural skill and attentional control.

6. Limitations

This study has several limitations. First, it was conducted in a simulated environment that may not fully replicate the complexities of real-world driving. Driver behaviors observed in the simulator may not accurately reflect their actual responses in authentic driving scenarios.

Second, the present study assessed training effects only immediately after the intervention; this limits conclusions regarding the long-term retention and real-world skill transfer of KAP training. Future longitudinal studies are needed to determine whether the observed improvements persist and whether they transfer to on-road driving scenarios. For example, following previous longitudinal studies (Allen et al., 2011; Glassman et al., 2022; Hanowski & Morgan, 2015), follow-up simulator sessions weeks or months after the participants received training can be conducted, either in a driving simulator or in naturalistic driving sessions (with drivers' takeover performance monitored with in-vehicle data recorders). Further, although participants received modest compensation (80 RMB per hour), there is a potential incentive-induced bias, such as increased motivation during the experiment, which, again, can be better evaluated in naturalistic driving sessions.

Next, the participants in our study were exclusively novice drivers, given that more novice drivers will begin owning their first vehicles with automation and may exhibit potentially risky attention allocation strategies when using automation. It should be noted that although we focused on novice drivers in the present study, the KAP training may also apply to experienced drivers, though the effectiveness may differ. For example, experienced drivers' superior ability to develop situational awareness of the traffic environment (He & Donmez, 2019) may facilitate faster takeover actions and thus overshadow the effectiveness of the KAP training. Experienced drivers are also known to better manage distractions in both vehicles with and without driving automation (He et al., 2022); thus, they may exhibit smaller differences when presented with ET and ST distractions. At the same time, cultural and demographic factors may moderate the effectiveness of training. For example, older drivers and drivers from regions with different traffic regulations, driving habits, or automation adoption rates (e.g., Europe vs. China) may differ in their baseline trust in automation (Du et al., 2022); thus, the attitude component of KAP training may have different effects. Future research should therefore examine the applicability of KAP training across diverse populations (e.g., older and experienced drivers, and drivers from other regions) to determine whether tailored modifications are needed to optimize its benefits in real-world application.

Finally, due to the simplified scenario design, we adopted only the five-region AOI scheme, which cannot quantify how the training program may affect drivers' attention to safety-critical objects, such as lead vehicles or lateral obstacles. Future studies employing more complex scenarios with latent hazards and richer road elements, and finer-grained AOIs (e.g., Huang et al., 2024) would allow a more direct assessment of whether KAP training improves semantic scene understanding at the object level, beyond the scanning patterns documented in this study.

7. Conclusions

Previous research on enhancing drivers' hazard perception has primarily focused on improving drivers' mental models and responsibilities when using automation, with little attention to takeover skills. In this study, we used a driving simulator experiment to evaluate the immediate effectiveness of the Knowledge–Attitude–Practice (KAP) framework in improving drivers' takeover performance. We found that:

- Both KA and KAP facilitated safer attention allocation strategies, as indicated by a lower frequency of long (>2 s) NDRT glances and increased attention to driving-related areas. This effect was more pronounced when drivers were given self-paced tasks, underscoring the importance of both driver training and task design in SAE L3 vehicles.

- KAP training, on top of KA training, significantly broadened drivers' scanning area and increased attention allocated to rear-view mirror monitoring, potentially enhancing drivers' ability to perceive hazards in peripheral areas.
- Both KA and KAP led to earlier first looks at the roadway and shorter takeover reaction times, highlighting that attitude-oriented training is critical for helping drivers quickly reallocate attention to driving and make decisive takeover actions.
- KAP yielded smaller lateral lane offsets than BA or KA, indicating that the practice component of the training can improve drivers' vehicle control capabilities in takeover events. Such an improvement was more likely to be realized through the procedural skill improvements than via trust-related changes.
- The KAP reduced drivers' subjective workload relative to KA and BA, a finding further supported by a smaller increase in heart rate during the takeover process than BA, indicating a greater confidence in handling takeover events after KAP training.

In summary, the results demonstrate the immediate effects of KAP training: the knowledge, attitude, and practice components can improve takeover performance in SAE L3 vehicles, even when drivers are distracted. Though the long-term effects of the training need to be further validated, the KAP training targeting takeover skills can be considered in addition to the mental model training (e.g., Huang et al., 2024) and responsibility training (e.g., DeGuzman & Donmez, 2024) of ADAS users to improve the safety of SAE L3 vehicles.

CRediT authorship contribution statement

Ange WANG: Data curation, Methodology, Software, Validation, Formal analysis, Writing – original draft. Zhenyu WANG: Data curation, Software. Song YAN: Data processing, Software. Dengbo HE: Conceptualization, Methodology, Writing – review & editing, Funding acquisition, Supervision. Hai YANG: Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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